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AI-Enabled Healthcare Resource Optimization for Intelligent Emergency Response and Clinical Service Management

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Abstract
The patient-flow characteristics within an emergency-department dataset and assess their relevance to evidence-based healthcare resource planning and intelligent clinical-service management. To characterize demographic, admission, waiting-time, satisfaction, and departmental patterns and identify operational indicators that may support future healthcare resource planning and decision-support development. The analysis identified an almost balanced pattern of admission outcomes, together with variation in waiting time, patient satisfaction, and departmental service utilization. General Practice represented the largest identified referral category, while Neurology showed the greatest mean waiting-time burden. Gastroenterology demonstrated the most favorable satisfaction level, whereas Renal recorded the lowest satisfaction despite having the shortest mean waiting time. These findings indicate that patient-flow characteristics vary across clinical-service categories and that no single indicator is sufficient to describe operational conditions. Examining patient volume alongside admission patterns, waiting time, and satisfaction provides a broader perspective on service demand and patient experience. The results therefore highlight potentially useful operational signals for healthcare managers when assessing departmental performance and planning future service improvements. The study demonstrates that routinely collected patient-flow information can provide a useful empirical foundation for evidence-based emergency-service planning and intelligent decision support. Future research should integrate real-time operational data, resource-capacity information, predictive modelling, and optimization techniques to develop actionable resource-allocation strategies.

Keywords: Artificial intelligence, Emergency healthcare, Patient flow, Resource planning, Waiting time

1. Introduction

Healthcare systems face growing operational pressure as patient demand increases, populations age, and emergency events become harder to anticipate. These pressures are particularly evident in emergency departments (EDs), where patient arrivals, clinical requirements, waiting times, and service availability can vary considerably over short periods (Achanta, 2025). Artificial Intelligence (AI) has consequently attracted substantial attention as a means of supporting healthcare organizations through data-driven analysis, predictive modelling, intelligent decision-making, and improved operational coordination (Arshad *et al.*, 2026). AI-enabled approaches have been associated with opportunities to
improve hospital efficiency, strengthen service management, and support the use of operational information for healthcare decision-making (Adari, 2020). The broader development of intelligent healthcare infrastructures has also connected AI with disaster preparedness, smart-city services, and real-time healthcare delivery (Abdul *et al.*, 2024).

Emergency healthcare presents a particularly challenging environment for resource management; service demand is uncertain, and operational decisions must frequently be made under time constraints (Pradhan *et al.*, 2023). Overcrowding, variable patient arrivals, limited workforce capacity, and the need to coordinate emergency services can place considerable pressure on existing management approaches (Alshammari *et al.*, 2024). Recent research has examined AI applications for emergency medical decision support, response-time improvement, workforce coordination, and intelligent ambulance management. AI has also been considered in disaster-management environments where rapid identification of changing conditions and efficient deployment of available resources are important for reducing response delays (Bhimavarapu, 2026). In addition, systematic work on AI-based emergency response systems has highlighted the potential of intelligent technologies to improve situational awareness and strengthen the resilience of emergency infrastructure.

The value of AI in emergency healthcare is not limited to physical emergency response. Data-driven methods can also support the analysis of patient movement, service demand, waiting times, admission behaviour, and clinical-service utilization. The application of edge AI to autonomous ambulance-route resource recommendations, while Chidananda *et al.* (2025) investigated AI-driven ambulance and traffic-control mechanisms for emergency response. During large-scale events, the complexity of healthcare delivery increases further; patient demand can change rapidly across locations and service categories. Alquayt *et al.* (2025) examined AI-driven healthcare innovations for mass gatherings and emphasized the potential of intelligent technologies for improving clinical-service coordination. These developments illustrate that AI can connect operational information with emergency-care planning across different healthcare contexts.

At the organizational level, AI can also contribute to broader healthcare performance improvement. AI as a mechanism for improving operational efficiency, patient care, and decision-making, whereas investigated AI-enabled digital-twin approaches for computational resource management in healthcare environments (Katal, 2024). Such approaches demonstrate the wider potential of combining data, intelligent algorithms, and operational management. Similarly, Kumar *et al*. (2026) examined predictive approaches for healthcare resource optimization in pandemic scenarios, while Cavadi (2025) proposed an AI-enhanced performance-management perspective for strengthening healthcare organizational resilience. These studies suggest that AI-supported management can move healthcare planning from predominantly reactive practices toward more evidence-based and adaptive approaches.

Despite this progress, an important gap remains between AI-oriented healthcare frameworks and the practical analysis of routinely collected patient-flow information. Existing work frequently concentrates on specialized applications, including ambulance routing, emergency response, pandemic preparedness, digital twins, or organizational resilience. Comparatively less attention has been directed toward examining routinely recorded indicators such as patient encounters, admission status, waiting time, satisfaction, and departmental referral can jointly describe operational conditions within emergency clinical services. Conceptual work by Nihi *et al*. (2025) has emphasized the importance of combining predictive analytics with healthcare optimization have explored integrated healthcare management using AI, real-time optimization, and multi-criteria decision analysis. However, empirical patient-flow analyses remain important for establishing the operational evidence required before more advanced optimization systems can be implemented.

Patient-flow analysis provides an important foundation for this purpose; it enables healthcare organizations to examine how demand and service characteristics vary across time and clinical categories. Recent systematic research has emphasized the importance of appropriate methods for analysing patient flow across healthcare settings. In emergency-care environments, AI and machine-learning approaches are increasingly being investigated for patient-flow prediction and operational improvement. The machine-learning predictions could be incorporated into an emergency-department patient-flow framework to improve throughput. Other recent reviews have similarly identified AI applications in admission prediction, waiting-time estimation, triage, and patient-flow management.

The study takes a more focused empirical approach. Rather than claiming direct optimization of staffing, beds, or other physical resources, it examines patient-flow characteristics that can provide operational evidence for future data-driven healthcare resource planning. This distinction is important because descriptive indicators such as patient volume, waiting time, admission status, satisfaction, and departmental referral do not themselves constitute a mathematical optimization model. Instead, they provide measurable information about demand, service activity, and patient experience that can support the development of more advanced AI-enabled decision-support systems. This perspective is consistent with the broader movement toward AI-assisted emergency patient-flow management while maintaining a clear distinction between analytical assessment and implemented resource optimization.

Accordingly, this study positions patient-flow analysis as an empirical foundation for intelligent emergency-service and clinical-service management. The analysis uses a dataset of emergency-department encounters to examine demographic characteristics, admission patterns, waiting-time behaviour, satisfaction levels, and departmental differences. By identifying variations in these indicators, the study seeks to demonstrate that routinely available healthcare data can reveal operational patterns relevant to service planning and resource-management decisions. The approach therefore connects empirical patient-flow assessment with the broader objective of developing resilient, evidence-based, and patient-centred healthcare systems. The objectives of this study are to characterize demographic, admission, waiting-time, satisfaction, and departmental patient-flow patterns within the emergency-department dataset and to identify operational indicators and departmental variations that can provide an evidence-based foundation for healthcare resource planning and decision support.

2. Materials and Methods

2.1 Study Design

This study employed a quantitative observational design to analyse patient-flow characteristics relevant to emergency clinical-service management. The analysis focused on patient demographics, admission status, waiting time, satisfaction scores, and department referral patterns. Descriptive and comparative analyses were used to characterize the study population and identify variations in clinical-service activity. The analytical framework was structured to examine patient volume, waiting-time behaviour, admission patterns, and patient experience across service categories. These indicators were selected to provide an evidence-based understanding of patient-flow characteristics and their potential relevance to healthcare service planning and operational decision-making. The methodological focus is consistent with established approaches to analysing healthcare patient flow.

2.2 Data Description

The study dataset comprised 9,216 anonymized patient encounter records from emergency department activity during 2023–2024. The recorded variables included patient identifier, admission date, admission time, gender, age, race, department referral, admission status, patient satisfaction score, and waiting time. These variables enabled assessment of demographic characteristics, admission distribution, patient volume, waiting-time patterns, and satisfaction across clinical-service categories. The dataset was analysed to describe overall patient-flow characteristics and department-level differences. Where individual variables contained missing observations, available records were used for descriptive statistics. Analyses requiring complete information across variables were performed using the complete-case subset obtained after data preprocessing.

2.3 Data Preprocessing

Before analysis, the dataset underwent preprocessing to ensure consistency of the recorded variables. Admission dates and times were converted into appropriate date and time formats. Admission-status values were standardized into "Admitted" and "Not Admitted." Patient identifiers were cleaned by removing hyphens, and duplicate patient identifiers were removed. Missing values were not replaced through imputation; instead, complete-case analysis was applied for analyses requiring all relevant variables. After removing records containing missing values, 1,077 complete observations remained. The cleaned dataset was subsequently used for the relevant statistical and analytical procedures. This preprocessing approach was applied consistently before examining patient-flow, departmental, waiting-time, satisfaction, and admission-related characteristics.

2.4 Descriptive and Department-Level Analysis

Descriptive statistics were calculated to characterize the study population and clinical-service activity. Continuous variables were summarized using means, standard deviations, medians, and ranges, while categorical variables were summarized using frequencies and percentages. Department-level analysis examined patient encounter volume, waiting time, and satisfaction across recorded referral categories, including General Practice, Orthopedics, Physiotherapy, Cardiology, Neurology, Gastroenterology, and Renal services. Encounters without a recorded department referral were also retained in the analysis. These comparisons were used to identify differences in patient volume, service waiting time, and reported satisfaction between clinical-service categories.

2.5 Patient-Flow and Temporal Analysis

Patient-flow patterns were further examined according to admission status, admission timing, waiting time, satisfaction, and department referral. Admission activity was assessed across the available observation period to identify variations in service demand, including monthly and yearly patterns for selected departments. Waiting-time measures were compared between referral categories, while satisfaction scores were examined to identify differences in reported patient experience. Relationships among selected patient-flow variables were also explored using correlation analysis. These analyses were intended to identify operational patterns that may be relevant to emergency-service planning and clinical resource management. The interpretation of patient-flow indicators was informed by established research on data-driven emergency-department flow optimization.

3. Results

3.1 Overall Patient Characteristics and Service Utilization

The demographic and clinical-service characteristics of the 9,216 recorded patient encounters. The mean patient age was 39.86 ± 22.76 years, with a median of 39 years and an observed range of 1–79 years, as shown in Table 1. The gender distribution was relatively balanced, comprising 4,729 male patients (51.31%) and 4,470 female patients (48.50%), while 17 records (0.18%) belonged to another recorded category. Admission outcomes were nearly equal, with 4,612 patients (50.04%) admitted and 4,604 (49.96%) not admitted. Mean waiting time was 35.26 ± 14.74 minutes, and satisfaction scores were available for 2,517 encounters.

Table 1. Patient Demographic and Clinical-Service Characteristics

Variable	Category	Result
Total encounters	—	9,216
Age (years)	Mean ± SD	39.86 ± 22.76
	Median	39
	Range	1–79
Gender	Male	4,729 (51.31%)
	Female	4,470 (48.50%)

	Other recorded category	17 (0.18%)
Admission status	Admitted	4,612 (50.04%)
	Not admitted	4,604 (49.96%)
Waiting time (min)	Mean ± SD	35.26 ± 14.74
	Median	35
	Range	10–60
Satisfaction score	Mean ± SD	4.99 ± 3.14
	Median	5
	Available observations	2,517
Department referral	General Practice	1,840 (19.97%)
	Orthopedics	995 (10.80%)
	Physiotherapy	276 (3.00%)
	Cardiology	248 (2.69%)
	Neurology	193 (2.09%)
	Gastroenterology	178 (1.93%)
	Renal	86 (0.93%)
	No referral recorded	5,400 (58.59%)

Source: *Authors' analysis of the study dataset.*
Note: *Variables were selected to characterize patient demographics, admission status, waiting time, satisfaction, and department referral, consistent with established approaches to patient-flow analysis (Yang et al., 2026).*

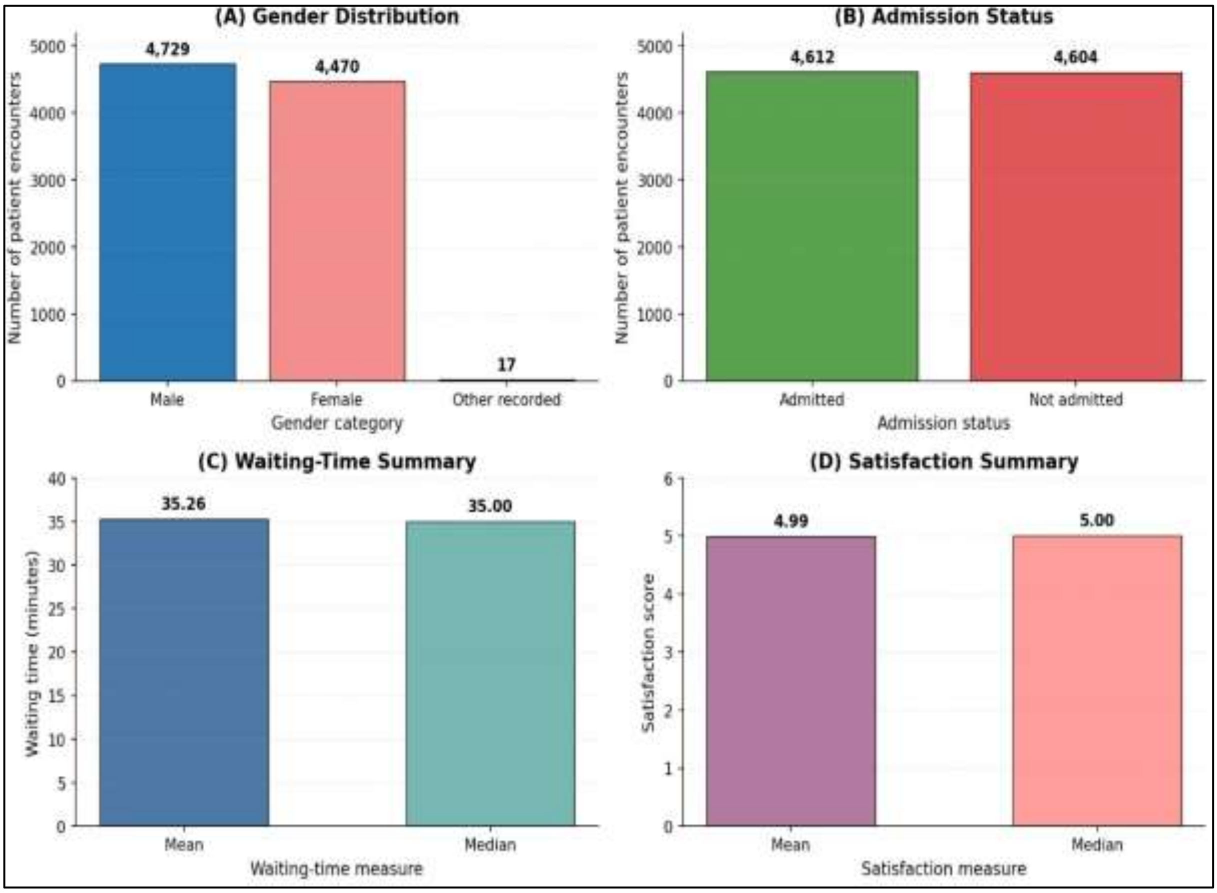

Figure 1. Patient Demographic and Clinical-Service Characteristics

The study comprised 9,216 patient encounters, with an average patient age of 39.86 years (SD = 22.76) and a median age of 39 years. Male patients accounted for 51.31% of the records, compared with 48.50% female patients and 0.18% in another recorded category as shown in Figure 1. Admission outcomes were almost evenly divided, with 4,612 patients (50.04%) admitted and 4,604 (49.96%) not admitted. The mean waiting time was 35.26 minutes, while the median was 35 minutes. Satisfaction scores were available for 2,517 encounters, with a mean score of 4.99 and a median of 5. These findings describe a relatively balanced patient-flow profile.

3.2Departmental Variation in Patient Flow and Service Experience

The differences in patient volume, waiting time, and satisfaction across the recorded department referrals. General Practice accounted for the largest referred patient volume, with 1,840 encounters, followed by Orthopedics with 995 encounters, as shown in Table 2. Neurology showed the highest mean waiting time at 36.80 minutes, while Renal recorded the lowest at 34.70 minutes. Satisfaction scores also differed across departments. Gastroenterology reported the highest mean satisfaction score of 5.80, whereas Renal had the lowest value of 4.57. Physiotherapy and Neurology showed comparatively longer waiting times than several other departments. These variations indicate differences in service utilization and patient experience across clinical-service categories.

Table 2. Department-Level Patient-Flow and Clinical-Service Indicators

Department referral	Patient encounters, n	Mean waiting time (min)	Median satisfaction score
General Practice	1,840	34.91	5.06
Orthopedics	995	34.98	4.86
Physiotherapy	276	36.57	4.99
Cardiology	248	35.35	5.14
Neurology	193	36.80	5.28
Gastroenterology	178	35.83	5.80
Renal	86	34.70	4.57
No referral recorded	5,400	35.29	4.95

Source: *Authors' analysis of the study dataset.*
Note: *Department-level waiting-time and patient-flow indicators are reported to assess variation in service demand and operational performance, consistent with data-driven approaches to emergency-department patient-flow optimization (Hodgson et al., 2025).*

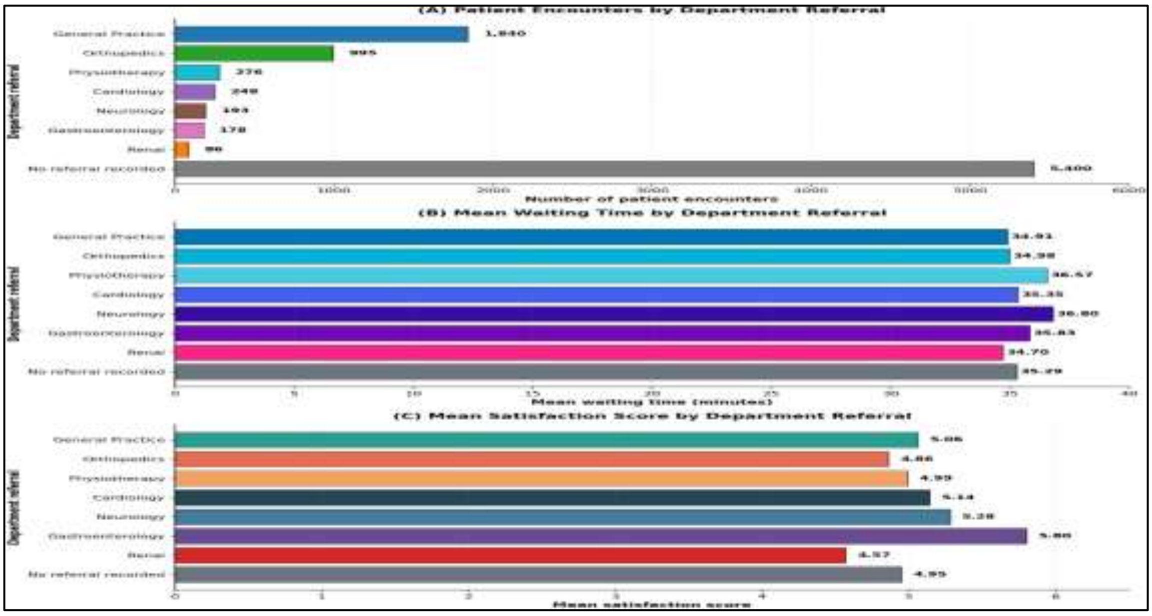

Figure 2. Department-Level Patient Flow and Clinical Service Indicators

The patient encounters, mean waiting time, and mean satisfaction scores across department referral categories. The largest number of encounters was recorded for patients with no referral (5,400), followed by General Practice (1,840) and Orthopedics (995), as shown in Figure 2. Mean waiting time varied moderately, with Neurology showing the highest value (36.80 minutes) and Renal the lowest (34.70 minutes). Satisfaction also differed between departments. Gastroenterology recorded the highest mean satisfaction score (5.80), whereas Renal showed the lowest score (4.57). Physiotherapy and Neurology had relatively higher waiting times, while Gastroenterology demonstrated comparatively favorable satisfaction. The figure highlights differences in patient demand and service experience across departments.

3.3Summary of Patient-Flow Indicators for Resource Planning

The main patient-flow measures relevant to healthcare resource planning. The dataset included 9,216 patient encounters, with a mean waiting time of 35.26 minutes and a median of 35 minutes as shown in Table 3. Admission outcomes were almost evenly distributed, with 4,612 patients admitted and 4,604 not admitted. Satisfaction scores were available for 2,517 patients, producing a mean score of 4.99 and a median of 5. At the department level, Gastroenterology recorded the highest satisfaction (5.80), while Renal recorded the lowest (4.57). Neurology had the highest mean waiting time (36.80 minutes), whereas Renal had the lowest (34.70 minutes).

Table 3. Patient-Flow Indicators Relevant to Healthcare Resource Optimization

Indicator	**Result**
Total patient encounters	9,216
Mean waiting time	35.26 min
Median waiting time	35 min
Waiting-time range	10–60 min
Total admitted patients	4,612 (50.04%)
Total non-admitted patients	4,604 (49.96%)
Patients with available satisfaction scores	2,517
Mean satisfaction score	4.99
Median satisfaction score	5
Highest department satisfaction	Gastroenterology (5.80)
Lowest department satisfaction	Renal (4.57)
Highest department mean waiting time.	Neurology (36.80 min)
Lowest department mean waiting time.	Renal (34.70 min)

Source: *Authors' analysis of the study dataset.*
Note: *The selected patient-flow indicators reflect their relevance to data-driven emergency-care management and patient-flow optimization (Hodgson et al., 2025).*

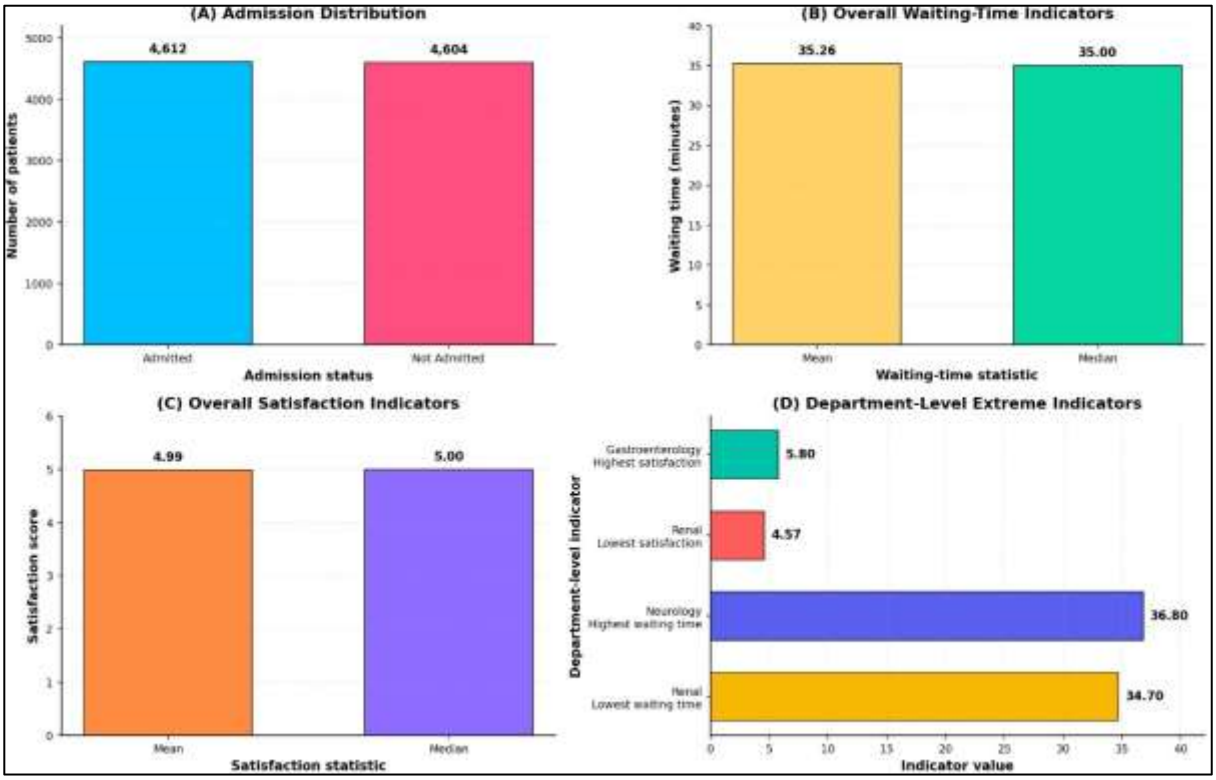

Figure 3. Patient Flow Indicators Relevant to Healthcare Resource Optimization

The key patient-flow measures associated with healthcare resource planning. The admission distribution was nearly balanced, with 4,612 patients admitted and 4,604 not admitted. Mean and median waiting times were similar at 35.26 and 35.00 minutes, respectively, as shown in Figure 3. Satisfaction scores also showed minimal difference between the mean (4.99) and median (5.00). At the department level, Gastroenterology achieved the highest satisfaction score (5.80), whereas Renal recorded the lowest (4.57). Neurology had the highest mean waiting time (36.80 minutes), while Renal had the lowest (34.70 minutes). These findings highlight measurable differences in patient experience and waiting times across clinical-service areas.

4. Discussion

The study provides an empirical assessment of patient-flow characteristics relevant to emergency and clinical-service management. Among 9,216 patient encounters, admission outcomes were almost evenly distributed, with 4,612 patients (50.04%) admitted and 4,604 (49.96%) not admitted. The overall mean waiting time was 35.26 minutes, with a median of 35 minutes and a range of 10–60 minutes. Satisfaction scores were available for 2,517 encounters, producing a mean score of 4.99 and a median of 5. These findings indicate a relatively balanced admission profile while showing that waiting time and patient experience remain important indicators for service assessment.

Departmental analysis revealed meaningful differences in patient volume, waiting time, and satisfaction. General Practice recorded the largest identified referral volume (1,840 encounters), followed by Orthopedics (995), whereas Renal had only 86 encounters. However, lower patient volume did not necessarily correspond to better service experience. Renal recorded the lowest satisfaction score (4.57), while Gastroenterology achieved the highest (5.80). Neurology had the highest mean waiting time (36.80 minutes), whereas Renal had the lowest (34.70 minutes). This suggests that patient volume alone cannot adequately represent departmental performance and that multiple indicators should be considered simultaneously.

The findings support the broader movement toward data-driven healthcare management. Ahmed *et al*. (2023) demonstrated that edge AI could support ambulance-route resource recommendations, while others examined AI-enabled ambulance and dynamic traffic-control mechanisms. These studies primarily address emergency response outside the hospital, whereas the present study focuses on patient-flow information within clinical services. All three approaches emphasize the importance of using operational information to support timely healthcare decisions. The current findings are also consistent with Almawkaa *et al*. (2025), who examined AI applications for decision support and response-time optimization in emergency services. The present study similarly identifies waiting time and admission outcomes as useful operational indicators. However, it does not establish that these indicators result from specific resource constraints. Behura (2024) highlighted intelligent ambulance-service management, demonstrating the wider relevance of computational approaches to emergency healthcare. AI-supported healthcare coordination during mass gatherings, where demand can vary substantially across services. Although the present dataset does not represent a mass-gathering environment, the departmental differences observed here similarly demonstrate that service demand and patient experience can vary across clinical categories. Bajwa (2025) further emphasized AI-enabled emergency response and rapid resource deployment, supporting the relevance of timely operational information for emergency preparedness.

At the hospital-management level, Puttanapura *et al*. (2025) described AI as a means of improving efficiency, patient care, and decision-making, while examining predictive approaches for hospital resource optimization. The present findings provide a preliminary empirical layer for these approaches by identifying demand, waiting-time, admission, and satisfaction patterns. Musham *et al*. (2026) similarly emphasized the relationship between predictive analytics, optimization, and decision-making. Unlike those broader frameworks, the present study does not directly implement mathematical resource optimization.

The findings have practical implications for healthcare service planning. Patient volume can help identify departments requiring routine capacity monitoring, while waiting-time measures can highlight services requiring workflow assessment. Satisfaction adds a patient-centred perspective that complements operational measures. Reshma Soman *et al*. (2025) emphasized AI-driven resource allocation for hospital operations, and the present results indicate basic patient-flow indicators could provide inputs for such future systems. The findings also support the development of intelligent decision-support platforms. Shaffi (2020) proposed AI-based emergency decision support, while Rathi *et al*. (2021) demonstrated the relevance of intelligent and connected healthcare infrastructures. The present study can therefore be viewed as an initial analytical layer that converts routinely collected patient information into interpretable operational evidence (Sodhro and Zahid, 2021).

Several limitations should be acknowledged. First, the observational design does not establish causal relationships between waiting time, satisfaction, admission, and departmental characteristics. Second, satisfaction information was available for only 2,517 of the 9,216 encounters, limiting interpretation of patient-experience findings. Third, staffing levels, bed availability, triage severity, treatment complexity, and real-time capacity were not included. Consequently, the study cannot determine whether specific departments were under-resourced. Finally, the analysis provides evidence relevant to resource planning but does not directly optimize staffing, beds, or other resources.

Future research should integrate real-time patient arrivals, staffing availability, bed occupancy, triage information, and treatment requirements with the current indicators. Predictive models could forecast departmental demand and waiting times, while optimization algorithms could translate those predictions into resource-allocation recommendations. Jameil and Al-Raweshidy (2024) demonstrated the potential of digital-twin approaches for computational healthcare resource management, while Utsho *et al*. (2026) highlighted AI applications for emergency resource allocation. Building on these directions, future studies should conduct prospective validation and evaluate outcomes such as waiting-time reduction, throughput, resource utilization, and patient satisfaction. This would advance the present evidence-based analysis toward a more comprehensive AI-enabled healthcare resource-management framework.

5. Conclusion

This study examined patient-flow characteristics within an emergency-department dataset to identify operational patterns relevant to healthcare resource planning and intelligent clinical-service management. The findings showed an almost balanced pattern of admission outcomes and highlighted variation in waiting time, patient satisfaction, and departmental service utilization. General Practice recorded the highest number of identified referrals, while Neurology showed the greatest waiting-time burden among the departments examined. Gastroenterology demonstrated the most favorable satisfaction level, whereas Renal recorded the lowest satisfaction despite having the shortest mean waiting time. These findings indicate that patient demand, waiting time, admission outcomes, and patient experience should be considered together when assessing healthcare service conditions. The study therefore provides a practical evidence base for future data-driven emergency-service planning and decision-support development. The present analysis does not directly implement mathematical resource optimization or determine specific staffing and bed requirements. Future research should integrate real-time operational information, resource-capacity measures, predictive modelling, and optimization techniques to translate observed patient-flow patterns into actionable resource-allocation strategies. Overall, the study demonstrates the value of systematically analysing routinely collected healthcare information as a foundation for developing responsive, evidence-based, and intelligent healthcare management systems.

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